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Estimating petroleum exergy production and consumption using vehicle ownership and GDP based on genetic algorithm approach

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Abstract

This study deals with exergy estimation of petroleum using genetic algorithm (GA) approach. The exergy estimation is carried out based on the gross domestic product (GDP) and the percentage of vehicle ownership figures in Turkey. Genetic Algorithm EXergy Production and Consumption (GAPEX) is developed. During the estimation of petroleum exergy, the GA is combined with time-series approach. For exergy consumption, three forms of the GAPEX are developed, of which one is linear, the second is exponential and the third is quadratic form of the equations. Among them, the best fit models in terms of average relative errors for the testing period are selected for future estimation. It may be concluded that the models proposed here can be used as an alternative solution and estimation techniques for available estimation techniques.

Keywords: Genetic algorithm; GA; Energy; Energy demand; Energy planning; Energy modeling; Exergy; Exergy modeling; Future projections; Turkey

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Contents

1. Introduction

Energy is the vital basis of the development of human society, and is associated with several aspects of the social activities and daily life. With increasing world population and rising living standards, the demand for energy is steadily increasing in the world. As energy is an important resource and has immense power, its cheap and stable supply is necessary to safeguard the economy and social development. Developing countries face the double pressure of economic growth and environmental protection as they enter the 21st century. Energy exploitation and utilization should be based on sustainable development and better ecological environment in developing countries, so that we can attain the objective of coordinating relationships among society, economy, energy and sustainable environment that meet the needs of the present without compromising the ability of future generations to meet their own needs [1–4].

Energy modeling is a subject of widespread current interest among engineers and scientists concerned with problems of energy production and consumption. Modeling in some areas of application is now capable of making useful contributions to planning and policy formulation [5]. In this regard, energy planning is not possible without a reasonable knowledge of past and present energy consumption and likely future demands [6].

Any method used to estimate the effects of policies and measures has to embody assumptions of one kind or another regarding the way measures will affect firm and consumer behavior, equipment turnover, and the introduction of new technology. Engineering models are usually based on the assumption that

technology is chosen and used to minimize system-wide discounted costs in meeting a given set of energy service demands. Input–output models are based on assumed or estimated production functions for each industry or process modeled. National energy models tend to have econometrically derived energy demand equations rather than include explicit representations of industrial technology [7].

Genetic algorithms (GAs) are random search techniques in solution space and they take the notion of Darwinian evolution of individuals. They are search and optimization procedures motivated by natural principles and selection. GAs have been successfully applied to a wide range of problems from image processing in medicine [8] to the optimal power flow [9] and determination of heat transfer coefficients [10]. Interest is also growing within the studies performed in the energy-related fields, such as nuclear energy [11–13], solar energy [14,15], low energy design in buildings [16] and cogeneration [17]. However, its use in modeling and estimating the energy demands is very limited [18,19], while its application to the estimation of exergy utilizations is quite new, as proposed in the following sections of the present study.

2. Genetic algorithm

The basic principles of the GA are attributed to Holland [20] and further developed for engineering applications by Goldberg [21]. The motivation of using the GA is due to globality, parallelism, and robustness of the GAs. In addition, GAs are simple yet powerful in their search for improvement and are not fundamentally limited by restrictive assumptions about the search space. The GA manipulates a population of candidate solutions to a problem. The candidate solutions are typically binary strings, but any representation may be used. At every generation, some of the candidate solutions are paired and parts of each individual are mixed to form two new solutions; this is *crossover*: crossover exchanges individual bits. Additionally, every individual is subject to random change—*mutation*. The next generation is produced by selecting individuals from the current one on the basis of their fitness, which is a measure of how good each candidate solution is. Eventually, the population should become saturated with individuals of very high fitness.

Consider a population of pz binary string individuals of length l. The strings correspond to chromosomes; atomic regions in the strings correspond to genes. There may be several variants of each gene: a particular version is called an allele. We define the fitness of the xth individual, $F(x)$, as an arbitrary function mapping the space $(0, 1)^n$ onto $(0, 1)$. The population is a panmitic unit, i.e. every individual has an equal probability of mating with any other. This probability is the crossover rate. All individuals are also subject to mutation at a relatively low rate. At the end of each generation, all parents and offspring are subject to tournament selection [21], allowing more fit individuals to increase their representation in the population. The selection process used in this study is *tournament selection* with replacement [22]. It chooses randomly a number of individuals from a population. It

selects the best individual from this group for further genetic processing, replaces the old chromosomes with new chromosomes, and repeats as often as required until the mating pool is filled.

GA applies the principles of the survival of the fittest. It tends in probability to select stronger dynasties in proportion to their fitness, leaving the weaker ones to wither away in probability. This means that while the GA tends to select superior dynasties, the best is not always selected and the worst is not always excluded. However, in contrast to more conventional gradient-type algorithms, which search from one single point to the next, GA applies the principles of selection, crossover and mutation to check whether new and better strains and varieties of model specification happen to exist. Selection and crossover enable the fitter strains to float to the surface, while mutation process prevents GA from getting stuck on inferior solutions. Moreover, it carries out this task efficiently because GA does not proceed model by model as an exhaustive search, but by model class. This reduces the need to sift through numerous individual models, which happen to belong to an inferior class. Goldberg [21] and Gen and Cheng [23] have succinctly summarized GA's efficiency in numerical optimization.

The key feature of a GA is the manipulation of a population whose individuals are characterized by possession of a chromosome. The chromosome consists of a string of characters, in this case bits, which describe the individual. The link between the GA and the problem at hand is provided by the fitness function (F). F establishes a mapping from the chromosome to a set of real numbers. The greater the value of F, the better is the adaptation of the individual.

The procedure is generative. It makes use of three main operators: reproduction, crossover, and mutation. Each generation of a GA consists of a new population produced from the previous generation. The pz individuals are assigned allelic values to their chromosomes, where the assignment can either be deterministic or random. Reproduction is a process that selects the fittest chromosomes according to some selection operator, such as tournament selection [22]. This operator chooses the members that will be allowed to reproduce during the current generation. Further manipulation is performed by the crossover and mutation operators before replacement of members in the next generation.

Crossover provides a mechanism for the exchange of chromosomes between mated parents. Mated parents then create a child with a chromosome that is some mix of the parents' chromosomes. For example, Parent#1 has chromosome 'abcde', while Parent#2 has chromosome 'ABCDE'; one possible chromosome for the child is 'abcDE', where the position between the 'c' and 'D' chromosomes is the crossover point.

Mutation is an operator which produces spontaneous random changes in various chromosomes. A simple way to achieve mutation would be to alter one or more genes. The mutation operator serves a crucial role in GAs either by: (a) replacing genes lost from the population during the selection process or (b) providing genes that were not present in the initial population. The mutation process has a small probability that (after crossover) one or more of the child's chromosomes will be mutated, e.g. the child ends up with 'abcDF'. The purpose of this operator is to prevent the process becoming trapped at a bad local optimum.

2.1. Representation

The representation of the coefficients of the GAPEX into binary strings requires determining the bit string length. The lower bound value corresponds to all zero digits (0000...), while the upper bound value corresponds to all one digits (1111...). The values between the lower and upper bound are linearly scaled and associated to corresponding binary strings.

Let $\psi = (w_1, w_2, \ldots, \phi_k)$ be the whole vector of weighting variables and $\psi_{\min}$ and $\psi_{\max}$ be the lower bound and upper bound vector of those variables. Then, stacking of design variables can be represented as follows:

$$\begin{array}{lllll} \text{Decision variables} & \psi = |w_1| & & |w_2| & |w_k| \\ \text{Mapping} & \downarrow \quad \downarrow & & \downarrow & \downarrow \\ \text{Chromosome (string) } x & = |01010101 & |01010111,\ldots,10101011 & |10101010,\ldots\ldots,01010010| & \end{array}$$

While dealing with binary string representation, one may need to use large number of bits to represent the variables to high accuracy. The number of binary digits needed for an appropriate representation can be calculated from the following equation:

$$2^{l_i} \geq \frac{\psi_{i,\max} - \psi_{i,\min}}{\Delta\psi_i} + 1; \qquad i = 1, 2, 3, \ldots, k \tag{1}$$

where $\Delta\psi_i$ is the precision of design variable and can be calculated as: $\Delta\psi_i = (\psi_{i,\max} - \psi_{i,\min})/(2^{l_i} - 1)$, where l_i is the required number of binary digits, and k is the total number of design variables. Although a higher degree of precision can be obtained by increasing the string length, it is not always desirable because computational cost of GAs also increases as the binary string gets longer.

Mapping from a binary string of design variables to real numbers is carried out in the following way:

$$\psi_i = \psi_{i,\ \min} + \beta_i \frac{\psi_{i,\ \max} - \psi_{i,\ \min}}{2^{l_i} - 1}; \qquad i = 1, 2, 3, \ldots, k \tag{2}$$

where β_i is the integer resulting from binary representation of the decision variables and k is the number of design variables at each form of the GAPEX model.

With previous operations, a population is changed in form and characteristics, and represents a new generation. Iterative search after many generations of evolution leads the population to an optimal design. Although the operations mentioned above can improve the designs as a collective population and, consequently, also best design, optimization searches are generally more interested in finding the best design. The elitist strategy that retains the current best individual to next generation without altering any information is a relatively easy operation that facilitates the search process.

The GA works with the expression operation that is performed based on fitness evaluation. The fitness indicates the *goodness* of design, and therefore, the objective function is a logical choice for the fitness measure. The fitness function, $F(i)$, selected in this study is to minimize total sum of squared error (SSE) between

observed and estimated values of exergy as follows: The fitness function takes the following form:

$$\text{Max } F(i) = \frac{1}{\sum_i^N s_i \times (E_{\text{obs}} - E_{\text{est}})^2}, \qquad i = 1, 2, \ldots, m \tag{3}$$

where E_{obs} and E_{est} are the observed and estimated energy demands, respectively, N is the number of observations, s_i is the weighting factor which is taken as 1 for this study although the other values of s_i are possible to improve convergence of the GAPEX models.

The three forms of the GAPEX models seek the most fit members by minimizing the error between observed and estimated energy and exergy values. The algorithm randomly selects a set of models and evolves them to create the best model. The three forms of the GAPEX models are given for exergy consumption in the following way:The linear form of the $\text{GAPEX}_{\text{lin}}$ models for exergy consumption is:

$$Y = w_1 + w_2 X_1 + w_3 X_2 \tag{4}$$

The exponential form of the $\text{GAPEX}_{\text{exp}}$ is:

$$Y = w_1 + w_2 X_1^{w_3} + w_4 X_2^{w_5} \tag{5}$$

The quadratic form of the $\text{GAPEX}_{\text{quad}}$ is:

$$Y = w_1 + w_2 X_1^{w_3} + w_4 X_2^{w_5} + w_6 X_1 X_2 \tag{6}$$

where Y is the estimated exergy consumption in PJ, X_1 is the GDP in 10^9\$, and X_2 is the percentage of vehicle ownership per person.

The GAPEX_{TS} model for exergy production is in the following form:

$$Y = w_1 X + w_2 X^2 + w_3 \exp(w_4 + w_5 X) + w_6 X^{w_7} \tag{7}$$

where Y is the estimated exergy production in PJ and X is the time series such that 1990 = 1, 1991 = 2,..., 2000 = 11.

3. Model development

The three forms of the GAPEX models are developed for petroleum exergy consumption in Turkey using GDP and vehicle ownership figures. The reason for developing these three forms GAPEX is to find the best fit equations to the observed data in terms of the SSE. Note that the best fit equation is selected for future projections of exergy consumption modeling. The general solution algorithm of the GAPEX in the three forms follows the following procedure.

Let $\mathbf{X}_t$ be a potential solution matrix of dimension $[pz \times l]$ for the GA random search space, where $j = (1, 2, 3, 4, \ldots, N)$, $\mathbf{x} = (0, 1, 0, 1, 0, 1, 0 \ldots, l)$, and l is the total number of binary bits in the string (i.e. chromosome), and let t be the generation number, where $t = (1, 2, 3, \ldots)$.

Step 0 *Initialization*. For given lower ($\psi_{\min}$) and upper ($\psi_{\max}$) bounds of GAPEX models for each equation, represent the weighting parameters as binary strings to form a chromosome **x.**

Step 1 Generate the initial random population of model parameters $\mathbf{X}_t$; set $t = 1$. There are no clear theoretical formulae that exist for the appropriate population sizing, but Carroll's [24] suggestion for this kind of problems is between 40 and 50.

Step 2 Decode all model parameters using Eq. (2) to map the chromosomes to the corresponding real numbers.

Step 3 Calculate the fitness functions for each chromosome x_j using Eq. (6).

Step 4 Reproduce the population according to the distribution of the fitness function values.

Step 5 Carry out the crossover operator by a random choice with probability of crossover (p_c). Based on previous studies, Goldberg [21] and Carroll [24] set the p_c between 0.5 and 0.6 for uniform crossover. Hence, p_c is selected as 0.5 in this study.

Step 6 Perform the mutation operator by a random choice with probability of mutation (p_m), then we have a new population. Probability of mutation (p_m) can be set to $1/pz$ [24].

Step 7 If the difference between the population average fitness and population best fitness index is less than 5%, restart population and go to the Step 1 and $t = t + 1$. Else, go to step 8.

Step 8 If t is maximal number of generation, the chromosome with the highest fitness is adopted as the optimal solution of the problem. Else, set $t = t + 1$ and return to Step 2.

4. GAPEX application and scenarios

The data are collected from different sources. The GDP, the petroleum exergy production and consumption values are collected from [25,26]. Numbers of vehicles are collected from the General Directorate of Turkish Highways (GDTH) [27]. Population number is collected from National Statistics [28]. The petroleum exergy production, consumption and their corresponding parameters are illustrated in Table 1 in the period of 1990–2000.

The three forms of the GAPEX models are performed with the following GA parameters:

Population size (pz)	50
Generation number (t)	250
Number of weighting variables (z)	3 for Eq. (4), 5 for Eq. (5), 6 for Eq. (6) and 7 for Eq. (7)
Probability of crossover (p_c)	0.5
Probability of mutation (p_m)	$1/50 = 0.02$

Table 1
Petroleum exergy production of Turkey and socio-economic indicators between 1990 and 2000

Years	Petroleum exergy production (PJ)	Petroleum exergy consumption (PJ)	GDP (10^9 \$)	Vehicle ownership (%)
1990	161.5	1084.70	152.39	5.28
1991	193.4	1101.70	152.35	5.75
1992	186.0	1163.30	160.75	6.42
1993	169.1	1150.20	181.99	7.35
1994	160.2	1179.60	131.14	7.76
1995	152.8	1189.90	171.98	8.07
1996	152.1	1227.30	184.72	8.45
1997	150.2	1258.80	194.36	9.07
1998	140.1	1336.20	205.98	9.60
1999	127.7	1259.30	187.66	9.98
2000	119.4	1207.20	201.48	10.59

The detailed weighting parameter, convergence proofs of the GA algorithm and its corresponding applications into the various engineering fields may be obtained [18,19,29,30].

4.1. Petroleum exergy modeling

4.1.1. Petroleum exergy consumption

The application of the linear form of the GAPEX$_{lin}$ model resulted in the following optimal-or-near optimal parameter values for the petroleum exergy consumption:

$$Y = 337.65 + 13.67X_1 + 77.77X_2 \tag{8}$$

The exponential form of the GAPEX$_{exp}$ is:

$$Y = 825.42 + 0.128X_1^{2.327} + 0.709X_2^{2.835} \tag{9}$$

The mix form of the GAPEX$_{quad}$ is:

$$Y = 636.55 + 3.975X_1^{1.408} + 9.479X_2^{1.832} - 0.686X_1X_2 \tag{10}$$

The application of the three forms of the GAPEX model results and the corresponding relative estimation errors are shown in Table 2. As can be seen from this table, the average relative errors on GAPEX$_{quad}$ are lowest compared to the others.

4.1.2. Petroleum exergy production

In order to estimate petroleum exergy production, the GAPEX$_{TS}$ model is used on the basis of time-series approach. The reason is that the petroleum exergy production is not dependent on the socio-economic indicators but only on own natural resources. Therefore, time-series (TS) expression is used for estimating the petroleum exergy production. Fig. 1 shows the fitted GAPEX$_{TS}$ for petroleum exergy production.

Table 2
The relative errors of energy production of Turkey between estimated and observed values

Years	Exergy (PJ)	$GAPEX_{lin}$ (PJ)	Relative error (%)	$GAPEX_{exp}$ (PJ)	Relative error (%)	$GAPEX_{quad}$ (PJ)	Relative error (%)
1998	1261	1366.01	−8.33	1404.84	−11.41	1380.82	−9.50
1999	1522.5	1370.06	10.01	1425.75	6.35	1396.76	8.26
2000	1462.8	1436.54	1.80	1535.64	−4.98	1478.78	−1.09
		Average = 6.71		Average = 7.58		Average = 6.28	

The application of the $GAPEX_{TS}$ model resulted in the following optimal-or-near optimal parameter values for the total energy consumption:

$$Y = -10.92X + 0.165X^2 + 4.13\exp(9.32 + 3.09X) - 38.97X^{-20.53} \tag{11}$$

The test period for the $GAPEX_{TS}$ is not used due to the rapid variations on the petroleum exergy production data in the period of 1990–2000.

5. Future projections

In order to make future projections for the total energy and exergy production and consumption of Turkey until 2020, the following is taken into account:

(a) The estimation of the GDP per year is given in Fig. 2, while Turkey's vehicle ownership figures are illustrated in Fig. 3.
(b) As can be seen in Table 3, the vehicle ownership figures of Turkey will rise to 17%, and the GDP is about 42.7 billion dollars.
(c) $GAPEX_{TS}$ is applied for estimating the petroleum exergy production of Turkey and the results are compared with the Ministry of Energy and Natural Resources (MENR) projections [25]. The three forms of the GAPEX are applied and comparisons are made with the MENR results for petroleum exergy consumption.

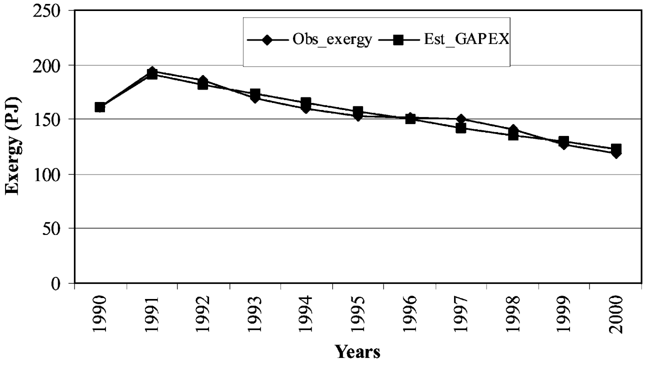

Fig. 1. Fitted $GAPEX_{TS}$ for petroleum exergy production.

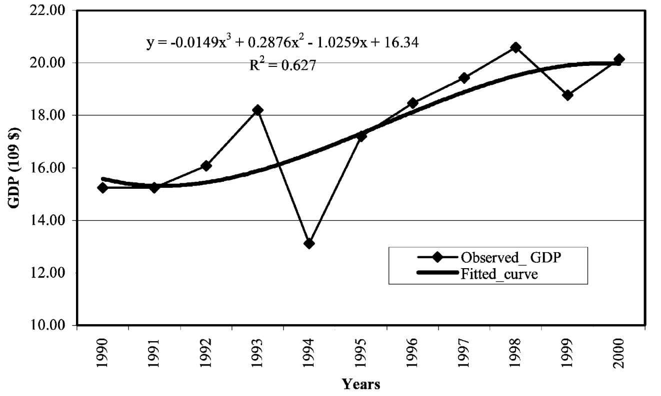

Fig. 2. Estimation of GDP.

5.1. Future estimation of exergy production

The estimated $GAPEX_{TS}$ results and the MENR projections are illustrated in Fig. 4. The $GAPEX_{TS}$ model estimates the exergy production two times higher than the MENR projection, as can be seen in this figure. The reason is that the sharp fluctuations on the measured exergy production in the years of 1990–2000, and the fluctuations on the MENR estimation in the years of 2000–2020. Although $GAPEX_{TS}$ estimate two times higher than MENR, it may be used as an alternative model to estimate petroleum exergy production of Turkey.

5.2. Future estimation of exergy consumption

The results of the three forms of the GAPEX are shown in Fig. 5 for Turkey's petroleum exergy consumption. The quadratic form of the $GAPEX_{exp}$ estimates

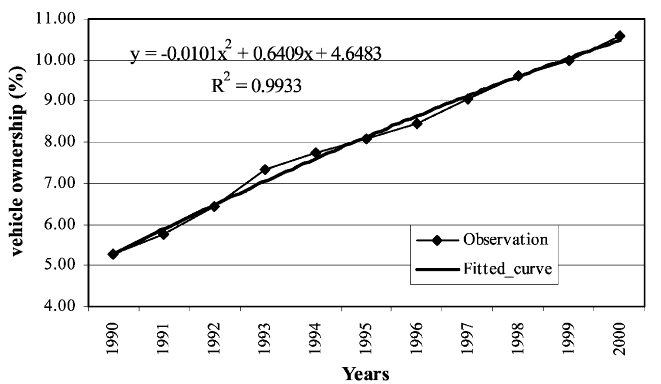

Fig. 3. Estimation of vehicle ownership figures.

Table 3
Estimated GDP and vehicle ownership

Years	GDP (10^9 \$)	Vehicle ownership (%)
2000	201.5	10.59
2005	246.4	12.50
2010	297.2	14.22
2015	357.2	15.72
2016	370.4	15.99
2017	383.9	16.26
2018	397.8	16.52
2019	412.0	16.78
2020	426.7	17.03

the exergy consumption values higher than MENR projections. $GAPEX_{quad}$ estimation is very close to the MENR projections. Note that the $GAPEX_{lin}$ estimation is lower than the MENR projections. Therefore, it can be proposed to estimate petroleum exergy consumption model for Turkey as an alternative to the MENR.

6. Conclusions

The estimation of petroleum exergy production and consumption is carried out in this study. In order to estimate petroleum exergy production, only one mathematical expression is used as a time series, and $GAPEX_{TS}$ is developed and proposed for future exergy estimation of Turkey. The three forms of the GAPEX models are developed for estimating the petroleum exergy consumption of Turkey and $GAPEX_{quad}$ is proposed to estimate future projections. All exergy models are developed based on the GA approach. The data are partly used for estimating the weighting parameters and partly for use in the model testing. The average relative errors between the observed and estimated values for each model are reported. The

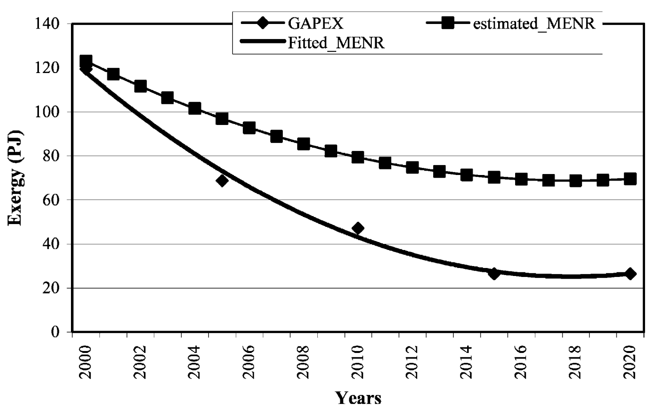

Fig. 4. Estimated petroleum exergy production of Turkey between 2001 and 2020.

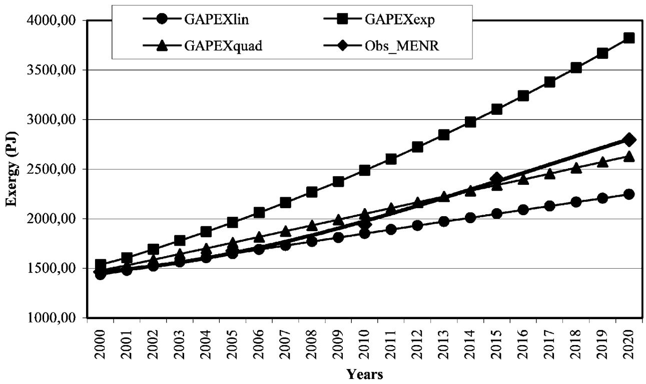

Fig. 5. Future projection of petroleum exergy consumption of Turkey until 2020.

trend line is fitted for estimating the GDP growth rate and the vehicle ownership figures of Turkey in the period of 2000–2020.

GAPEX models are flexible in nature to provide many near-optimal solutions to estimate the future trends of the petroleum exergy production and consumption values. This advantage comes from the GA approach itself, because the GAPEX models start the solution of the problem from a large population base. The model is actually a multi-parameter solution, which has many feasible solution points. Hence, the GAPEX models can be used for estimating the petroleum exergy demand in future by optimizing the parameter values using available data. Other advantage of the GAPEX models is that any type of mathematical representation can be solved with the GA approach provided that it appropriately represents the objective (fitness) function. As a result, the GA approach may be used to estimate the future trends of the petroleum exergy production and consumption of Turkey. The GAPEX models can be seen as an alternative model-fitting algorithm to the current data.

In this study, although the data are few to make concrete results about which form of the GAPEX models may be better to estimate the future estimation of petroleum exergy production and consumption of Turkey, this analysis can show that the GA can be used as an alternative solution algorithm to estimate the future demand of petroleum exergy. The models should be tested with more data (if possible).

The results of the present study are also expected to give a new direction to engineers, scientists, and policy makers in implementing energy and exergy planning studies as a potential tool.

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